

Smart Access System Using Face Recognition

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Abstract- Identifying a person with an image has been popularized through the mass media. However, it is less robust to fingerprint or retina scanning. This report describes the face detection and recognition mini-project undertaken for the visual perception and autonomy module at Plymouth university. It reports the technologies available in the Open-Computer-Vision (OpenCV) library and methodology to implement them using Python. For face detection, Haar-Cascades were used and for face recognition Eigenfaces, Fisherfaces and Local binary pattern histograms were used. The methodology is described including flow charts for each stage of the system. Next, the results are shown including plots and screen-shots followed by a discussion of encountered challenges. The report is concluded with the authors' opinion on the project and possible applications.

Key Words – Haar-Cascade, Face-Recognition, Computer Vision, Face detection.

1. Introduction

The following document is a report on the project for Robotic visual perception and autonomy. It involved building a system for face detection and face recognition using several classifiers available in the open computer vision library (OpenCV). Face recognition is an on-invasive identification system and faster than other systems since multiple faces can be analyzed at the same time. The difference between face detection and identification is, face detection is to identify a face from an image and locate the face. Face recognition is making the decision "whose face is it?", using an image database. In this project both are accomplished using different techniques and are described below. The report begins with a brief history of face recognition. This is followed by the explanation of Haar-cascades, Eigenface, Fisherface and Local binary pattern histogram (LBPH) algorithms. Next, the methodology and the results of the project are described. A discussion regarding the challenge and the resolutions are described. Finally, a conclusion is provided on the pros and cons of each algorithm and possible implementations.

2. The History of Face Recognition

Face recognition began as early as 1977 with the first automated system being introduced by Kanade

using a feature vector of human faces. [1] In 1983, Sirovich and Kirby introduced the principal component analysis (PCA) for feature extraction. Using PCA, Turk and Pentland Eigenface were developed in 1991 and is considered a major milestone in technology. Local binary pattern analysis for texture recognition was introduced in 1994 and is improved upon for facial recognition later by incorporating Histograms (LBPH) [2]. In 1996 Fisherface was developed using linear discriminant analysis (LDA) for dimensional reduction and can identify faces in different illumination conditions, which was an issue in Eigenface method. Viola and Jones introduced a face detection technique using HAAR cascades and ADABOOST. In 2007, a face recognition technique was developed by Naruniec and Skarbek using Gabor Jets that are similar to mammalian eyes [6]. In this project, HAAR cascades are used for face detection and Eigenface, Fisherface and LBPH are used for face recognition.

3. Face Detection using Haar-Cascades

A Haar wavelet is a mathematical function that produces square-shaped waves with a beginning and an end and used to create box-shaped patterns to recognize signals



with sudden transformations. By combining several wavelets, a cascade can be created that can identify edges, lines and circles with different colour intensities.

Figure 1: Several Haar-like-features matched to the features of authors face.

These sets are used in Viola Jones face detection technique in 2001 and since then more patterns are introduced for object detection.

To analyze an image using Haar cascades, a scale is selected smaller than the target image. It is then placed on the image, and the average of the values of pixels in each section is taken. If the difference between two values pass a given threshold, it is considered a match. Face detection on a human face is performed by matching a combination of different Haar-like-features.

For example, forehead, eyebrows and eyes contrast as well as the nose with the eyes as shown below in figure. A single classifier is not accurate enough. Several classifiers are combined to provide an accurate face detection system. [3]

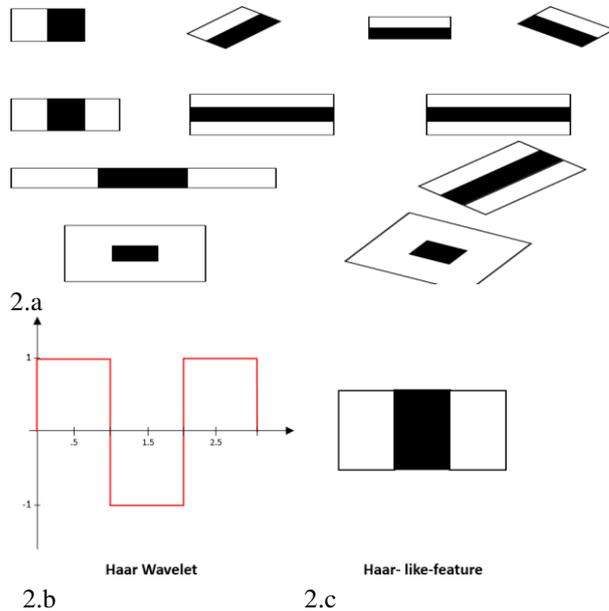
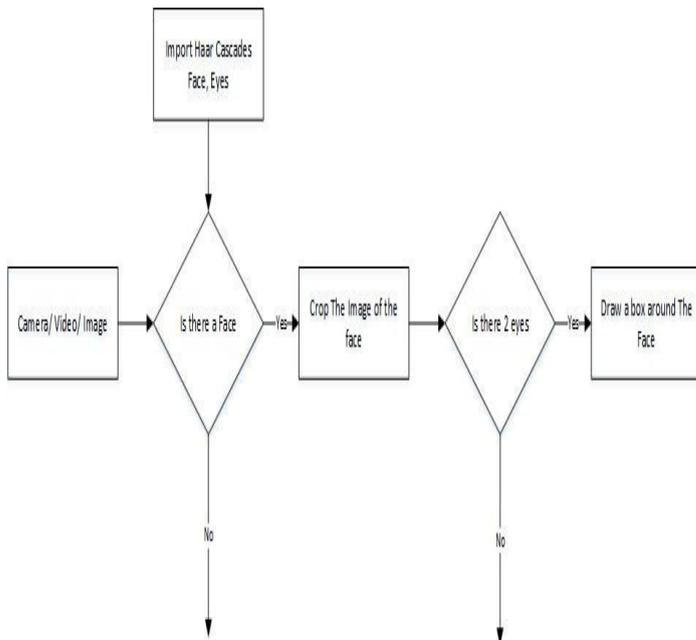


Figure 2a: Different Haar Features

Figure 2b: A Haar wavelet

Figure 2c: Resulting Haar-like features.

In this project, a similar method is used effectively to by identifying faces and eyes in combination resulting better face detection. Similarly, in viola Jones method,



several classifiers were combined to create stronger classifiers. ADA boost is a machine learning algorithm that tests out several weak classifiers on a selected location and chooses the most suitable. It can also reverse the direction of the classifier and get better results if necessary. Furthermore, Weight-update-steps can be updated only on misses to get better performance. The cascade is scaled by 1.25 and

re-

Figure 3: Haar-cascade flow chart

iterated in order to find different sized faces. Running the cascade on an image using a conventional loop takes a large amount of computing power and time. Viola Jones used an integral image to compute the matches fast. First developed in 1984, it became popular after 2001 when Viola Jones implemented Haar-cascades for face detection. [4] Using an integral image enables matching features with a single pass over the image.

4. Algorithm

- Face Detection and Data Gathering
- Train the Recognizer
- Face Recognition

The below block diagram resumes those phases:

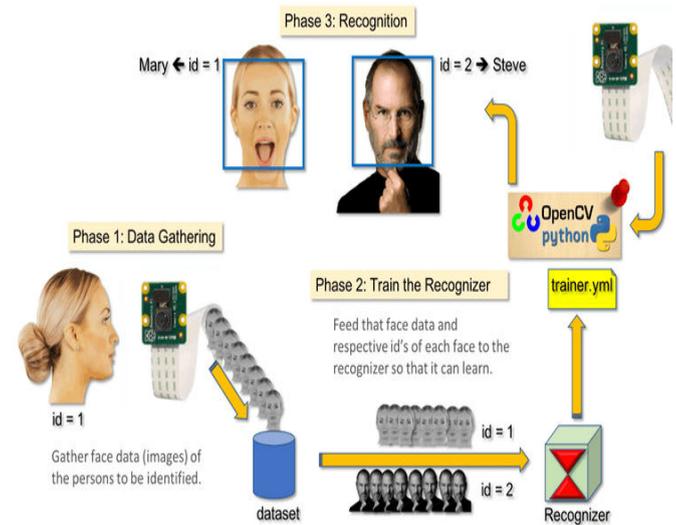


Figure 4: Algorithm of Face Recognition

5. Proposed Work

Below are the methodology and descriptions of the applications used for data gathering, face detection, training and face recognition.

The project was coded in Python using a mixture of IDLE and PYCharm IDEs.

Face recognition is different of face detection:

- **Face Detection:** it has the objective of finding the faces (location and size) in an image and probably extract them to be used by the face recognition algorithm.
- **Face Recognition:** with the facial images already extracted, cropped, resized and usually converted to grayscale, the face recognition algorithm is responsible

for finding characteristics which best describe the image.

FaceDetection

First stage was creating a face detection system using Haar-cascades. Although, training is required for creating new Haar-cascades, OpenCV has a robust set of Haar-cascades that was used for the project. Using face-cascades alone caused random objects to be identified and hence cascades were incorporated to obtain stable face detection. The flowchart of the detection system can be seen in figure.

Face and eye classifier objects are created using classifier class in OpenCV through the `cv2.CascadeClassifier()` and loading the respective XML files. A camera object is created using the `cv2.VideoCapture()` to capture images. By using the `CascadeClassifier.detectMultiScale()` object of various sizes are matched and location is returned. Using the location data, the face is cropped for further verification. Eye cascade is used to verify there are two eyes in the cropped face. If satisfied a marker is placed around the face to illustrate a face is detected in the location.

Face Recognition Process

For this project three algorithms are implemented independently. These are Eigenface, Fisherface and Linear binary pattern histograms respectively. All three can be implemented using OpenCV libraries. There are three stages for the face recognition as follows:

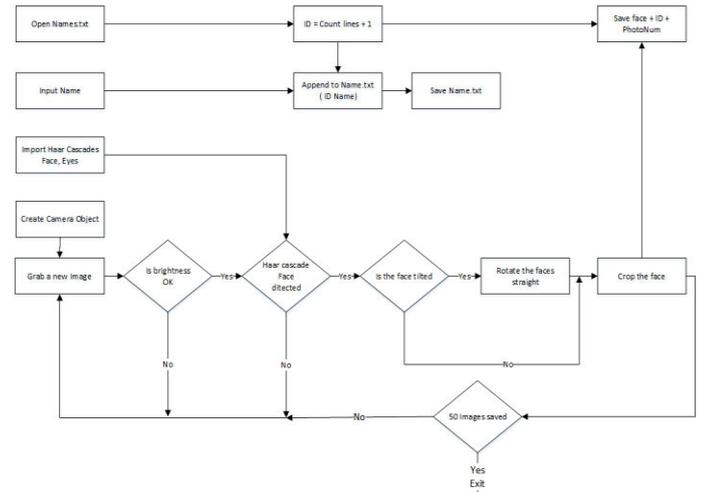
1. Collecting images IDs
2. Extracting unique features, classifying them and storing in XML files
3. Matching features of an input image to the features in the saved XML files and predict identity.

6. LBPH Algorithm

1. **Parameters:** the LBPH uses 4 parameters:
 - **Radius:** the radius is used to build the circular local binary pattern and represents the radius around the central pixel. It is usually set to 1.
 - **Neighbors:** the number of sample points to build the circular local binary pattern. Keep in mind: the more sample points you include, the higher the computational cost. It is usually set to 8.
 - **Grid X:** the number of cells in the horizontal direction. The more cells, the finer the grid, the higher the dimensionality of the resulting feature vector. It is usually set to 8.
 - **Grid Y:** the number of cells in the vertical direction. The more cells, the finer the grid, the higher the dimensionality of the resulting feature vector. It is usually set to 8.

2. Training the Algorithm: First, we need to train the algorithm. To do so, we need to use a dataset with the facial images of the people we want to recognize. We need to also set an ID (it may be a number or the name of the person) for each image, so the algorithm will use this information to recognize an input image and give you an output. Images of the same person must have the same ID. With the training set already constructed, let's see the LBPH computational steps. [10]

3. Applying the LBP operation: The first computational step of the LBPH is to create an



intermediate image that describes the original image in a better way, by highlighting the facial characteristics. To do so, the algorithm uses a concept of a sliding window, based on the parameter's radius and neighbors [5].

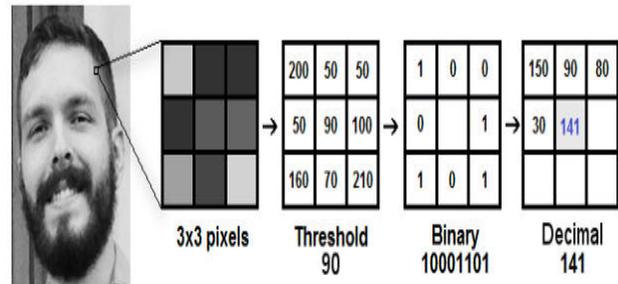
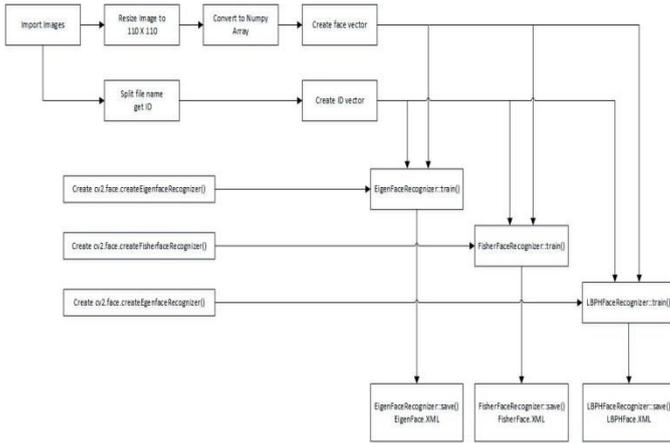


Figure 5: LBPH Algorithm [9]

Based on the image above, let's break it into several small steps so we can understand it easily: Suppose we have a facial image in grayscale.

- We can get part of this image as a window of 3x3 pixels.
- It can also be represented as a 3x3 matrix containing the intensity of each pixel (0~255).
- Then, we need to take the central value of the matrix to be used as the threshold.
- This value will be used to define the new values from the 8 neighbors. [8]

Figure 6: Flowchart for Image Collection



- For each neighbor of the central value (threshold), we set a new binary value. We set 1 for values equal or higher than the threshold and 0 for values lower than the threshold.
- Now, the matrix will contain only binary values (ignoring the central value). We need to concatenate each binary value from each position from the matrix line by line into a new binary value (e.g. 10001101). Note: some authors use other approaches to concatenate the binary values (e.g. clockwise direction), but the final result will be the same.
- Then, we convert this binary value to a decimal value and set it to the central value of the matrix, which is actually a pixel from the original image.[11]

Collecting the imagedata

Figure 7: The Flowchart for the image collection.

Collecting classification images is usually done manually using a photo editing software to crop and resize photos. [9] Furthermore, PCA and LDA requires the same number of pixels in all the images for the correct operation. This time consuming and a laborious task is automated through an application to collect 50 images with different expressions. The application detects suitable expressions between 300ms, straightens any existing tilt and saves them. The Flowchart for the application is shown in figure 7.

Application starts with a request for a name to be entered to be stored with the ID in a text file. The face detection system starts the first half. [12] However, before the capturing begins, the application checks for the brightness levels and will capture only if the face is well illuminated. Furthermore, after the face is detected, the position of the eyes is analyzed. If the head is tilted, the application automatically corrects the orientation. These two additions were made considering the requirements for Eigenface algorithm. The image is then cropped and saved using the ID as a filename to be identified later. A loop runs this program until 150 viable images are collected from the

person. This application made data collection efficient.

7. Results



Figure 8: 200 image training data in grayscale

```

    Console 1/A
    Python 3.7.3 (default, Mar 27 2019, 17:13:21) [MSC v.1915 64 bit (AMD64)]
    Type "copyright", "credits" or "license()" for more information.

    IPython 7.4.0 -- An enhanced Interactive Python.

    In [1]: runfile('C:/Users/kunal/Desktop/mp code/Face recognition
    dataset.py', wdir='C:/Users/kunal/Desktop/mp code')
    Face not Found
    Collecting Samples Complete!!

    In [2]: runfile('C:/Users/kunal/Desktop/mp code/Training New.py', wdir='C:/
    Users/kunal/Desktop/mp code')
    Model Training Complete

    In [3]:
    
```

Figure 9: Samples collected and Training model complete



Figure 10: No Capture if face not found

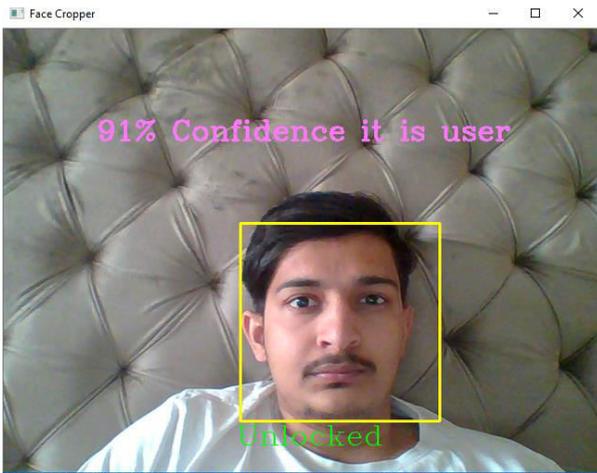


Figure 11: Face labeled for the detected person by the test-trained data.

8. Conclusion

This paper describes the mini-project for visual perception and autonomy module. Next, it explains the technologies used in the project and the methodology used. Finally, it shows the results, discuss the challenges and how they were resolved followed by a discussion. Using Haar-cascades for face detection worked extremely well even when subjects wore spectacles. Real time video speed was satisfactory as well devoid of noticeable frame lag. Considering all factors, LBPH combined with Haar-cascades can be implemented as a cost effective face recognition platform. An example is a system to identify known troublemakers in a mall or a supermarket to provide the owner a warning to keep him alert or for automatic attendance taking in a class.

9. References

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